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Use of Probabilistics in Campaign Analysis

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ABSTRACT

Significant advances have been made recently in applying probabilistic methods to aerospace vehicle concepts. Given the explosive changes that are occurring in today's political, social, and technological climate, it makes practical sense to try and extrapolate these methods to the campaign analysis level. This would allow the assessment of rapidly changing threat environments as well as technological advancements, aiding today's decision makers. The following paper summarizes attempts to apply these methods directly to campaign analysis, and discusses the resulting issues that were identified as potential problem areas. A new approach is postulated which includes the application of probabilistic methods to a fully linked analysis environment. Applying and validating these new methods is an ongoing project.

INTRODUCTION

In recent years, the world has been changing at a remarkable pace. A revolutionary new economy has risen. This economy is based on knowledge rather than conventional raw materials and physical labor [1]. With this new economy comes new emphasis on technology and its impact, especially in the warfighting environment. Almost all of the world's countries spend a significant amount of their budget on the research, development and procurement of increasingly sophisticated weapons and warfare technologies [2]. This is necessary because countries need to maintain or enhance their military capabilities in order to maintain their supremacy over their adversaries. In addition, strong and capable military capabilities serve as a deterrent to other countries who might otherwise turn aggressive. However, the high cost of maintaining these capabilities must be balanced against limited resources. Former U.S. Secretary of State Dick Cheney is credited with the statement "budget drives strategy, strategy doesn't drive budget" [1]. Military decision makers need to understand and assess the benefits and consequences of their decisions in order to make cost efficient, timely, and successful choices.

Along with changes in the world's economy come changes in the way war is fought. Substantial progress has been made in both weapon lethality and military technology. In addition, the battlefield of today has become increasingly complex, with interactions and their consequences becoming more and more difficult to isolate and understand. Because of the rapid advance of these developments, the decision makers are often left with ambiguous information and relatively short time spans to conduct analysis. Often, these changes occur so rapidly that previous analysis is rendered obsolete. For example, an aircraft that is designed to incorporate a certain avionics suite will often find that those avionics are obsolete by the time the aircraft comes into production. The inherent uncertainty in this information makes definitive analysis difficult and implies that the use of probabilistic methods to understand and interpret this information is most appropriate.

Understanding the sources of the uncertainty helps determine why a probabilistic approach is useful. Perfect knowledge about model inputs is rare, and it is often that the analyst or decision maker must make assumptions based on available data and personal experience. Using probabilistic inputs would allow the user to account for variation in his assumptions. Analysis based on these probabilistic inputs could provide useful information about the sensitivities of the inputs, which in turn could be translated into requirements definitions. By allowing the inputs to vary, the analyst or decision maker could play "what if" games, using the models as a computationally and economically inexpensive way to explore the boundaries of the problem. And finally, variable inputs would allow an investigation of the robustness of a

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solution (i.e. that solution whose performance parameters are invariant or relatively invariant to changes in its environment).

Another major source of uncertainty can be found when considering the incorporation of a new technology. Modeling current technologies is straightforward, with the performance parameters of that technology generally known. However, current technologies may not be capable of meeting customer needs or design goals. In addition, current technology may be obsolete by the time the system is implemented. This necessitates a prediction capability concerning the impact of new technologies. Performance of a new technology is a function of its readiness level, but that function may or may not be completely defined. By modeling a new technology in a probabilistic fashion, one can explore various assumptions pertaining to the performance and the corresponding effects of that technology.

Overall, the presence of uncertainty in most complex systems, including campaign analysis, makes the use of probabilistic methods a valuable analysis tool for today's military decision makers.

MODELS AND MODELING

In order to understand the role of probabilistics in campaign analysis, it is important to understand the nature of military modeling. A model can be defined as a purposeful abstraction of a more complex reality [3,4]. This reality could take the form of a real or imagined system, an idea, or a phenomenon or activity. The model tries to capture the essence of this reality in a simplified representation. A military model is specifically defined as "a representation of a military operation and is an abstraction of reality to assist in making defense-related decisions" [3].

Rather than being physical (iconic), most military models in use today are abstract, or mathematical, models. This kind of model uses symbols and logic to create an abstraction of reality. Mathematical relationships are often utilized to represent the dynamic properties of the object. Examples of an abstract model include an aircraft sizing and synthesis code, a biologic model that mimics population growth of bacteria, or an economic model of the stock market.

Abstract models are further divided into descriptive and prescriptive [3,5]. A descriptive model limits itself to replicating the behavior of what it is representing. As such, there is no value judgement placed on the behavior; no "goodness" or "badness" is represented. An example of a descriptive model is a combat simulation. Decisions based on information from descriptive models are made by inference, as there is no integral optimization structure inherent in the model. For example, a sizing and synthesis code, which is another example of a descriptive code, may indicate that an aircraft's gross weight is 35,000 pounds, but the model itself does not specify whether this is an acceptable value or not.

In contrast, a prescriptive model specifies a course of action, with an attached value judgement. A prescriptive model (sometimes called normative, which implies a representation of human behavior) may label an output as adequate, inadequate, or optimal. Linear programming, dynamic programming, game theory, and decision theory are all methodologies that indicate to their user an acceptable course of action. It is often difficult to separate a descriptive model from a prescriptive one. Descriptive models are often used prescriptively, to explore options and solutions by trial and error. Prescriptive models are often used for insight only, as some loss of fidelity is usually traded off in order to incorporate optimization schemes. The user of such models needs to understand the abilities and limitations of each model in order to utilize them accurately and effectively.

HIERARCHICAL MODELING - In addition to classifying military models according to their traits and characteristics, it is important to understand how these models relate to each other, and what their specific function is. A well known way of relating military models is to classify them as to their position in a defined hierarchy. This hierarchy is often portrayed as having a pyramidal shape (Figure 1) and is described by Hughes [3]: "Whatever the number of echelons that is included in it, the bottom will contain mainly phenomenological models and the top a single macro model. The pyramid may represent the nesting of models in one interacting, organic whole; show how results are integrated from echelon to echelon; or merely be an abstract representation of a structure that relates independent model operations."

Typically, a hierarchical structure will be divided up into three or four aggregate levels. Ziegler [6] first introduced the idea of decomposing models in a hierarchical manner that corresponded to levels of detail. Later, he described this decomposition as having as its first level the most abstract behavioral description of the system. This is followed by sub-systems levels of increasing detail, until a limit is reached and further decomposition is not justified [7]. This type of decomposition is echoed in the hierarchical structures of military models described today: the first level usually contains an encompassing theater or campaign level model, followed by engagement or mission models, with the lower levels being reserved for engineering sub-system models.

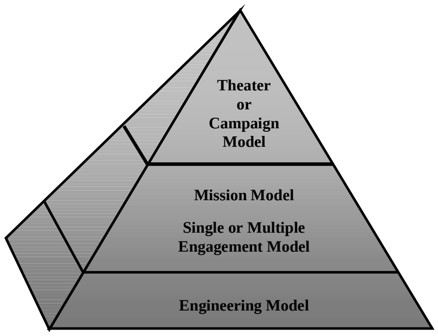

Figure 1- Traditional Pyramid of Military Models

DECOMPOSITION LEVELS - There are other examples of hierarchical levels [8,9] that are each different in their specifics, yet illustrate an interesting point: although each example chooses its own delineation for its levels, and names them correspondingly, each individual hierarchy does encompass the entire spectrum of relational military models and analysis, starting from a detailed, engineering type model and ending in an overall systems level model. In order to discuss and define these types of models, they will be divided into roughly three categories: engineering models, mission models, and campaign models. These model categories will now be discussed in more detail, with the understanding that they will overlap in definition as they pertain to individual hierarchies.

Engineering Models - The level that comprises the bottom of all hierarchies is that of engineering models. These are usually detailed mathematical representations of individual systems or components that may or may not be associated with a platform. For example, a hierarchy may consider a jammer or a sensor to be an engineering model, yet another hierarchy may lump them together onto a platform and have one model of that integrated system. Engineering models are usually physics-based, contain a high level of detail, and are of relatively short simulation timeframe. Inputs are usually design variables, sizing criteria, and new technologies. Basic mission requirements and constraints may be introduced at this level to aid in sizing. For example, an aircraft sizing and synthesis code typically needs a rudimentary mission profile to be input for sizing purposes. (An interesting investigation of the influence of mission requirements on the vehicle being sized can be found in [10].) Outputs of engineering models often consist of geometric dimensions and performance data.

Engineering codes are generally used to conduct tradeoff studies of design variables and technologies, and to calculate performance characteristics. These types of codes can usually be validated and they lend themselves well to real-world testing. However, analysis conducted using this type of model is limited to the scope of the model. For example, an airplane sizing and synthesis model can provide data about the performance of a particular aircraft, yet does not provide information as to how well that aircraft will aid in reaching system (theater or campaign) level goals. Figure 2, from Ref [8], shows the engineering level features.

Mission Models - The middle level of the traditional pyramid is occupied by mission models. These models, also referred to as engagement models, encapsulate one vs. one or many vs. many encounters of specific sub-system components. For example, a mission level code could be used to simulate air-to-air combat between multiple flights of aircraft. The focus on this level concerns the timing and details of a single mission. Scenario, strategy, support, and overall force capabilities are usually not considered [11]. The timeframe of mission models is usually at the hours or days level, and they involve a medium level of detail. The level of interaction is increased, and the model will usually contain aggregate systems and subsystems. Unlike the engineering models, mission models are more troublesome to validate, and data collection for input is often difficult. Figure 3 shows a representation of the mission level from Ref [8].

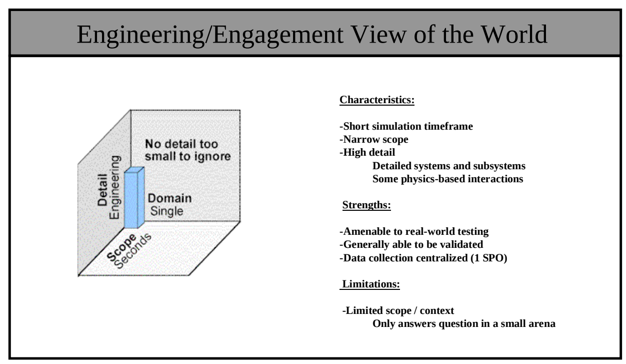

Figure 2- Engineering Level Model Features

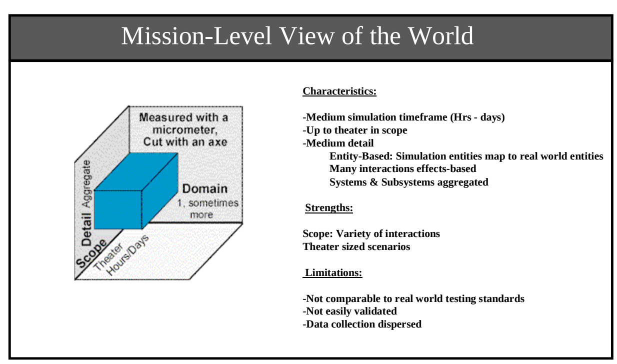

Figure 3- Mission Level Model Features

Campaign Models - Campaign models, also called force models or theater models, are usually large single codes that encompass the effects of the total forces involved, including air, ground, and naval, as well as coalition forces [11,12]. They are primarily used to answer questions and make decisions at the larger system level. For example, campaign analysis, aided by campaign models, is used to study the interactions of strategy, force allocation, and system capabilities. Other features that dominate analysis are the effects of command and control decisions, deployment and sustainment (logistics) issues, and the cumulative effects of decisions as considered in a time-spanning environment.

There are many campaign (or theater) level models in use today. It is common that certain organizations favor specific codes for their analysis needs, and these codes often emphasize, in terms of modeling detail and capability, a particular force. Some of the more well-used codes and the organizations that are their primary users are listed in Figure 4.

USN	USA	USMC	USAF	OSD
GCAM ITEM	TAC WAR VIC	COMBAT IV	THUNDER	TAC WAR ITEM

Figure 4- Common Campaign Codes in Use Today

There are inherent limitations to campaign models. The first is that an inordinate amount of experience and information is needed by the user to use them effectively: the quality of the analysis is often directly related to the experience of the analyst. In addition, considerable detail is needed in both the scenario definitions and in the component descriptions in order to have a complete analysis. Yet at the same time, the complexity and run time of the code necessitates that detail be kept at a minimum. Insight into strategic philosophy must also be considered. Another problem is the length of the campaign to be modeled. As the campaign time increases, difficulty in retaining fidelity of the model also increases. A key feature of campaign time is that as the campaign progresses, tactics and decisions evolve based on experiences and results so far [3]. This “human in the loop” problem is considered in more detail in subsequent sections. The campaign level is depicted by Ref [8] and is shown in Figure 5.

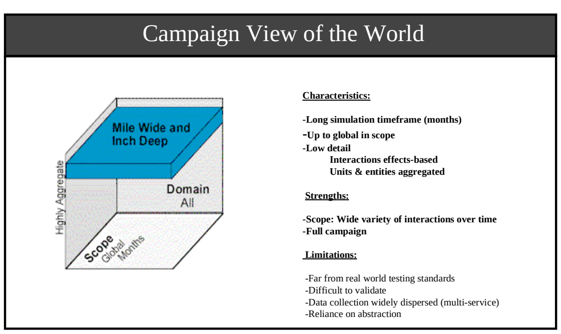

Figure 5- Campaign Level Model Features

THE CODE CONTINUUM – Given the features of each type of military model, the traditional pyramid formulation can be replaced and enhanced by a new concept, similar to that in Ref [8], of a military code continuum. Figure 6 shows this continuum, and illustrates the primary two analysis tradeoff of the continuum: as analysis moves from the engineering end of the spectrum to the campaign analysis end, the modeling codes increase dramatically in complexity yet lose an enormous amount of detail. This is a main reason that probabilistic methods are considered at the campaign level. The sheer number of entities that need to be modeled, coupled with an increasing number of decisions and interactions, soon lead to a modeling problem that is so complex that it becomes impractical to model the inputs with any level of detail. However, this necessary sacrifice of detail does come with a price. At the engineering level, where significant detail is captured, the resulting metrics are very specific. Questions can be answered precisely. As the analysis moves towards the campaign level, the metrics become increasingly amorphous, with results that are more subjective and provide insight rather than explicit answers.

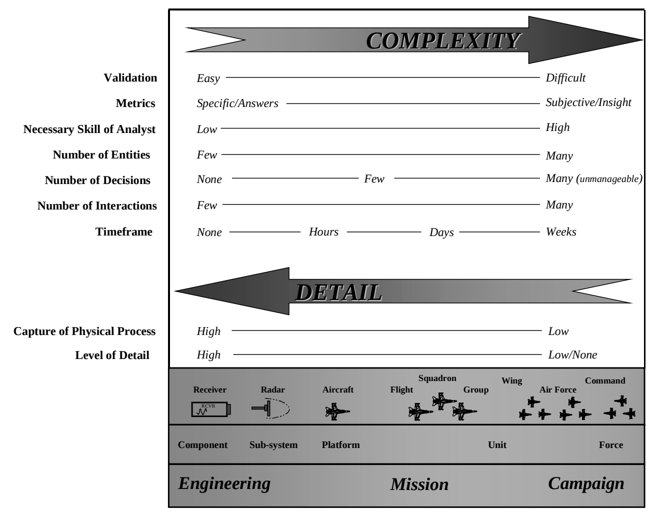

Figure 6- The Military Code Continiumm

PRELIMINARY INVESTIGATIONS

PROBABILISTIC METHODS AT THE ENGINEERING LEVEL – Much work has been done recently using probabilistic methods at the individual aerospace concepts level [13,14,15,16]. Metamodels based on regression methods have been created relating vehicle design variables (geometry, engine specifications, drag polars, etc) to vehicle responses (takeoff gross weight, thrust-to-weight ratio, etc.). Further advances in the methodology added economic variables, requirements and mission constraints, as well as allowing analysis of the effect of new technologies.

The cornerstone of these probabilistic methodologies is Response Surface Methodology (RSM) combined with Design of Experiments (DOE). RSM is an efficient, multivariable approach to system modeling that defines clear cause-and-effect relationships between design variables and system responses, and is based on a statistical approach to building and rapidly assessing empirical metamodels [17,18].

The RSM methodology, employing a DOE strategy, creates metamodels of a particular synthesis code by selecting a subset of all possible combinations of variables to run which will guarantee orthogonality (i.e. the independence of the various design variables). Using regression techniques, the subset of inputs are related to selected outputs to create an equation that represents the relationship between inputs and outputs of the synthesis code. This technique allows the maximum amount of information to be gained from the fewest number of experiment executions, and thus provides trade study results in a more cost-effective manner.

The first step in the creation of the metamodel is to select an appropriate Design of Experiments. This DOE is expressed as a table of experimental cases, specifying the values of the variables to be used for each individual execution of the synthesis code. These values are usually normalized to a low, high, or midpoint value of the variable (represented by a –1, 1, and 0 to aid in the statistical analysis). An example DOE table is shown in Table 1. Typically, the response is first modeled using a second order quadratic equation of the form:

$$R = b_o + \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{ii} x_i^2 + \sum_{i=1}^{k-1} \sum_{j=i+1}^{k} b_{ij} x_i x_j$$

R	is the desired response term
b_o	is the intercept term
bi	are regression coefficients for the first order terms
bii	are coefficients for the pure quadratic terms
bij	are the coefficients for the cross-product terms
x_i ,x_j	are the independent variables
k	is the total number of variables considered

This equation is called a Response Surface Equation (RSE). Other forms of the equation may be used (for example, during a screening test, a first order linear regression is appropriate). If the non-linearities of the problem are not sufficiently captured using this form of the equation, then transformations of the variables and/or the responses need to be found which improve the fidelity/accuracy of the model.

A Response Surface Equation (RSE) is created by executing multiple runs of the synthesis code, with each execution using as its inputs the values of the variables determined by the DOE table. The resulting responses of interest for each run are then collected from the output and added to the table (the blank columns in Table 1). A statistical analysis package (in this case, JMP [19]) provides the ability to take this data and perform a regression analysis to create these polynomial representations (Analysis of Variance or ANOVA) to determine these sensitivities, relative importance, fidelity, etc. JMP also aids in providing the experimental setup, as well as facilitating visualization of the results. There is one Response Surface Equation created for each response, and this equation is a function of all input variables. The resulting RSEs, thus, are in actuality metamodels of the synthesis code used in their creation. The equations represent a quick, accurate way of determining a response for given values of variables (as long as these values are within the range of variables for which the RSE is defined).

Table 1- Example Design of Experiments Table

Experimental Case	Factor 1	Factor 2	Factor 3	...Factor n	Response 1 (R_1)	...Response n (R_n)
1	-	-	0	-	R_{1-1}	R_{n-1}
2	-	+	0	+	R_{1-2}	R_{n-2}
3	+	-	0	0	R_{1-3}	R_{n-3}
4	+	+	0	+	R_{1-4}	R_{n-4}
5	0	-	-	0	R_{1-5}	R_{n-5}
6	0	-	+	0	R_{1-6}	R_{n-6}
7	0	+	-	-	R_{1-7}	R_{n-7}
8	0	+	+	-	R_{1-8}	R_{n-8}
9	-	0	-	+	R_{1-9}	R_{n-9}
10	+	0	-	-	R_{1-10}	R_{n-10}
11	-	0	+	0	R_{1-11}	R_{n-11}
12	+	0	+	-	R_{1-12}	R_{n-12}
...	...	...	...	...	...	...

The Response Surface Methodology is comprised of two basic steps, facilitated by the program JMP. The first is referred to as the effect screening. It creates a linear model which is used to determine the sensitivity of a response to various inputs and to screen out, using a Pareto analysis, those variables that do not contribute significantly to the variability of the response. The second step is called surface fitting, and yields a polynomial representation that gives the response as a function of the most important input parameters. These steps are illustrated in Figure 7.

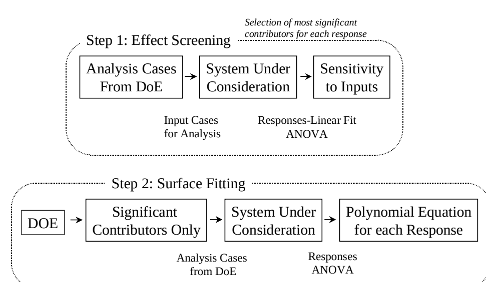

Figure 7- Basic Steps of Response Surface Methodology

The benefit of RSM is that it provides an almost instantaneous evaluation time. The equations are portable and can be run in a spreadsheet, a computer code, or even by hand. Within the variable ranges given, the results can be highly accurate. Caution should be exercised as to the ranges of applicability of these equations since they do not, as with all polynomials, extrapolate well. If variable values are needed outside the range of the RSEs generated, a new DOE experiment should be created and executed. In addition, the equations are continuous, and thus cannot account for discontinuities or higher order effects.

Prediction Profiles - Once the RSEs are created, JMP can then be used to create prediction profiles. These profiles allow the designer to see graphically how the responses vary with respect to changes in each of the variables. Figure 8 shows a sample prediction profile. The lines in Figure 8 denote the sensitivity of the response with respect to each variable. In essence, they are the partial derivatives of the response with respect to the variable with all other variables set at a given value. A flat or barely sloped line indicates that the variable does not have much impact on that response.

When using the prediction profile tool while in JMP (as opposed to a hard copy printout of the graph), the program allows the designer to change the value of the variables by using a click and drag technique. Using the RSEs, the graph is then updated in real time to show the new values of the responses. In this way the designer can manipulate the equations to gain insight into the problem and also to seek optimal configurations.

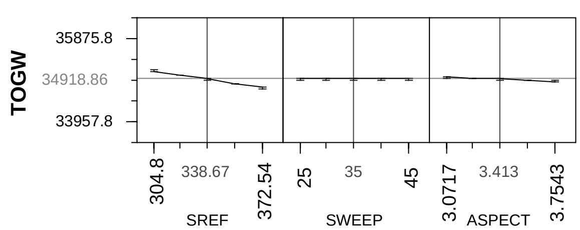

Figure 8- Example of a Prediction Profile

K_factors - Once the RSEs have been created, they can be manipulated in a multitude of ways. One common use for the RSEs is to explore the effects of varying the inputs probabilistically. For example, this technique could be used to model a new technology concept. A new technology concept is characterized by ambiguity and uncertainty with regards to its performance, cost, etc. In order to introduce these uncertainties into the model, variability must be added to each input variable. This variability may be modeled by creating a multiplier of a disciplinarian metric and putting a probability distribution around it. By using the RSEs in a Monte Carlo environment, the effect of this variability can be quantified. For example, Figure 9 shows a shape distribution for the multiplier, or K_factor, associated with wing weight. This particular shape distribution would be appropriate for a technology that is expected to give a 7.5% decrease in wing weight, yet recognizes, through the use of a skewed distribution, that there is some chance of achieving either a greater or lesser change in wing weight. Other distribution shapes that may be used include a uniform distribution, used for when each value is as likely as another value, or a normal distribution which is used when there is an equal uncertainty around a particular value. The K_factor concept is not limited to modeling technologies, but can be used whenever the impact of the variability of an input factor is desired.

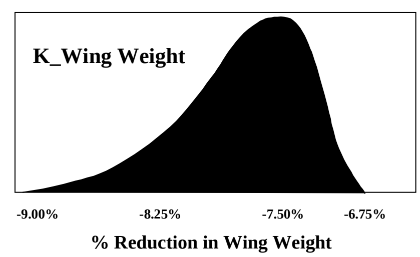

Figure 9- Notional Shape Function for a Wing Weight Reduction K_factor

Monte Carlo Simulation - After determining shape distributions for all of the variables, a Monte Carlo simulation, utilizing the Crystal Ball [14] software, is conducted. Variable values are chosen randomly based on the distribution given. The responses are then calculated through the use of the RSEs. The results are probability distributions that indicate the likeliness of achieving a certain result. Figure 10 shows examples of the two ways that the probabilistic results can be presented. The first is the probability density function (PDF), which depicts the frequency that a certain value is observed in the simulation. The second is the integral of the PDF, called the cumulative distribution function (CDF), which shows the probability or confidence of achieving a certain value. By examining the CDF in Figure 5, the designer can see that there is about a 10% chance of achieving a takeoff gross weight of 33,475 pounds or less, but a 100% chance of achieving a takeoff gross weight of less than 33,850 pounds (find 33,475 on the horizontal axis, follow it up to where it hits the curve, and read the corresponding probability from the vertical axis).

The designer can interpret information from the probability distributions in a number of ways. If the distribution has quite a bit of variability, but some or most of it fulfills the requirement being examined, this would suggest that the assumptions, including any technology infusions, are viable. It would be beneficial, therefore, to invest more resources into the technologies or options that the assumptions represent. This addition of resources could have the effect of narrowing the uncertainty associated with the technologies or options. On the other hand, if the distribution indicates that the probability of meeting the requirement is low, then it might be more provident to examine other options before investing money into a technology or decision that might not be sufficient to solve the problem. This kind of system-level investigation can also show how much the detrimental effects of certain decisions are penalizing the system. This information, shared with the disciplinary experts that engage in the development of the technologies or assumptions, could be investigated to see how resources need to be allocated towards reducing the penalties, as opposed to improving benefits.

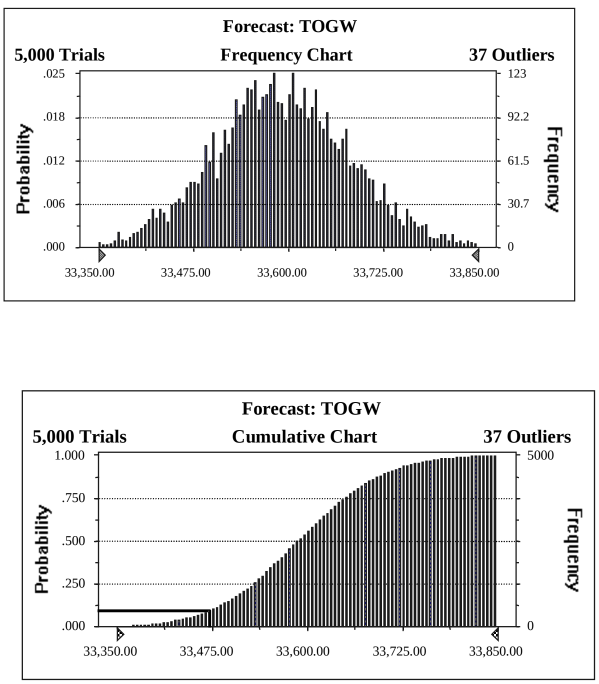

Figure 10- Examples of a Probability Density Function and a Cumulative Probability Function

EXTRAPOLATION TO CAMPAIGN ANALYSIS – Because of the success of applying probabilistic methods to aerospace vehicles, it became natural to try and extrapolate these proven methods from the engineering level models to campaign level models. This was done in an attempt to improve the quality of information provided to the decision makers discussed in the introduction. The RSM and DoE strategy was applied to the campaign analysis code ITEM [20] using a simplified air scenario. This preliminary research identified several key issues that limited the usefulness of using the probabilistic methods in their current form [21,22].

<u>Human in the Loop</u> - A major difference between vehicle level and theater level analysis codes is how the user interacts with the code. In a traditional vehicle sizing code, the user will supply a set of inputs and the code will iterate on a sizing scheme to converge the vehicle according to the laws of physics and empirical relationships. In ITEM and other similar theater codes, however, the user becomes an integral part of the analysis process. This means that the user periodically evaluates the effect of his/her decisions and can then change the parameters (either from that point or change initial input parameters and rerun the simulation) to provide improved results. ITEM was specifically designed to incorporate the use of human judgement to make strategic decisions based on the state of the forces at any given time. Figure 11 shows a typical analysis scheme for using a theater level code.

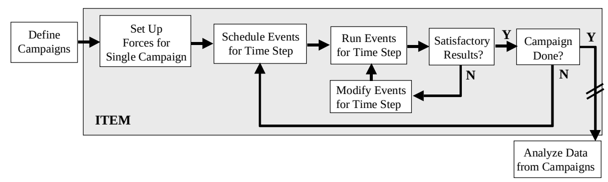

Figure 11- Flowchart for Decision-Making for ITEM [23]

The alternative to having the human in the loop is to use some sort of embedded rules (expert systems) to make decisions. There are some theater level codes that do this. The key drawback to this is that the rules have an inherent lack of flexibility to simulate real operational plans. In addition, these rules lack transparency in assessing cause and effect relationships. An example of this drawback in illustrated in the following example. Say that an embedded rule system is used to model the decisions made in a particular scenario. The results are summarized as follows: “The analysis shows that there is an 85% probability that this scenario (with its inputs) results in the loss of two aircraft carriers in the first four days of the event.” What is wrong with this statement? In the real world, losing two aircraft carriers is so completely unacceptable that, after the loss of the first carrier, **the decisions (inputs) would be changed** in order to ensure that a second carrier would not be lost. With embedded rules, unrealistic results such as these could be modeled and erroneous decisions based upon these results.

<u>Level of Detail</u> – The next key issue identified by the preliminary research was that of level of detail. As discussed in the military code continuum section, campaign analysis modeling necessarily includes a sacrifice of detail. While one way of accommodating this lack of detail is to use probabilistic inputs, this in itself has drawbacks. It was determined by the research that the ranges put on the input variables had a tremendous effect on the outputs. This is because in the campaign analysis tool itself, different sub-systems and entities were themselves modeled at differing detail levels. Therefore, a 5% change in input variables of one entity could differ dramatically from a 5% change in the input

variable of another, more detailed entity. This disparity could falsely skew results. The issue of detail, or lack thereof, also impacted the transparency of the campaign analysis. It was found in the research that the inputs, especially after being transformed into probabilistic inputs, could often not be easily identified in a cause and effect relationship with the outputs. It was often difficult to isolate input interactions.

<u>Fixed Scenarios</u> - Finally, it was found that the campaign scenario itself had a significant effect on the outputs. Usually when conducting a campaign analysis, a particular scenario is specified and used for the remainder of the analysis. Given a particular scenario, it can be fairly straightforward to optimize a technological and tactical solution. However, as discussed in the introduction, today's world is full of rapidly changing threats and technologies. An optimized solution for one particular scenario may differ dramatically from the solution to a subtly different scenario. This lack of robustness can have significant implications to today's decision makers, who need to consider a wide variety of ever changing threats and technological advances.

SYSTEM OF SYSTEMS APPROACH

After identifying the above issues, it was concluded that applying the current probabilistic methodologies in their existing form would not adequately provide the information that the decision makers needed. The proposed solution to the issues involved two key components: the creation of a linked analysis environment that itself was fully probabilistic. This new formulation involves system of systems concepts and is currently being implemented as part of the Probabilistic System of Systems Effectiveness Methodology (POSSEM) [21,22].

LINKED ANALYSIS ENVIRONMENT – The first issue to be tackled is the level of detail problem. It has been shown that the degree of detail lost at the campaign level is critically detrimental to the results. Yet at the same time, it is acknowledged that creating a campaign level tool that retains detail down to the sub-system (engineering) level is impractical and computationally expensive. The proposed solution to this dilemma involves the creation of a linked analysis environment. The first step in creating such an environment is a clear identification and understanding of the particular problem to be explored. This up front analysis determines what tools (models) need to be used as well as the pertinent levels of detail needed. Once these tools are selected, they are linked together either computationally or manually to form a complete analysis path that is robust in both detail and complexity. In other words, a linked analysis environment is a mini military code continuum that is specifically selected/designed to aid in the solution of a particular problem. This linked analysis environment is very similar to the concepts of model abstraction and software zooming [9,24,25].

Here is an example of a possible linked analysis environment. Suppose the problem under consideration is to gain insight into the effect of a new aircraft radar. Let's start at one end of the military code continuum. An engineering code that models the physics of the radar would seem like a good and necessary tool to use. However, just by itself, this tool could only give performance data of the radar. But in order to really assess the effect of this new radar system, it needs to be placed in its correct context: the radar needs to assigned to a platform, and that platform needs to be assessed as a component in the larger system, the warfighting environment. So by itself, this code does not provide the necessary information, even though the level of detail is superb. Moving to the other end of the continuum we may be tempted to start with a full blown campaign analysis code. This would give us information (metrics) at the needed system level. However, such a code will be so "top level" that any inputs for aircraft radar would be limited to one or two variables at most, if any inputs exist at all. What is needed, therefore, is a link between the two extremes. The detail of the engineering code is needed yet the data needs to be assessed at the system (campaign) level. It should be noted that a direct link between the two extremes is not practical, and indeed violates the military code continuum. There needs to be an intermediate code at the mission level. The radar needs to be placed on an aircraft and that aircraft needs to be placed into a one vs. one or few vs. few situation in order to assess this new system's performance. This data is then passed on to the campaign code. Because there is a clear analysis path from the campaign code all the way back to the radar code, transparency is enhanced and a proper assessment may be conducted.

The above linked environment sounds good in theory, and choosing and linking the codes computationally seems relatively straightforward. However, this analysis environment is only the first piece of the total solution. How this environment is used is important, and is crucial to the solution of the overall problem.

FULL PROBABILISTIC ENVIRONMENT – Now that the analysis environment has been created, the role of probabilistic methods within this environment can be discussed.

At the engineering level, the traditional RSM and DoE probabilistic methods will be applied, as discussed earlier. Using these methods at this level has shown a wealth of benefits, primarily allowing the analyst to assess the effects of new technologies applied at that level. In addition, sensitivities to design requirements can be explored, as well as determining mission requirements with their accompanying sensitivities.

Currently, there are no plans to use the extrapolated probabilistic methods at the mission level. This is primarily to simplify the methodology during its formative stages. A mission level code will be implemented to provided the transition from the engineering level code(s) selected to the campaign analysis code. It is understood, however, that once the proof of concept has been completed, the components of the methodology can be applied to any level of the continuum, including the mission level.

Let's return for a moment to the Human in the Loop problem discussed earlier, which occurs at the campaign level in the analysis. The question now becomes: how do we apply a probabilistic methodology if we need to maintain the information provided by having human in the loop? There are several possible approaches. The first of these is the simplest. Acknowledge the problem, but schedule the events and run the cases anyway. In other words, ignore the issue and continue. The unrealistic solutions and decisions are accepted and identified, while still gaining insight into the overall problem. In addition, care can be taken to try and eliminate unrealistic decisions through careful scheduling. If it is decided that it is important to include the issue, the next logical step is to use the concept of decision trees to schedule events, create nodes of key decisions, and examine all possible results.

The final decision of the authors was that the issue was important and crucial enough to address, and critical to the formulation of the new methodology. In addition to using decision trees to identify and model key decision points, the authors will explore the concept of Time-Dependant Response Surface Equations (TDRSEs). In the current methodology, there is a direct input-output relationship between the design variables and the response metrics of interest. A TDRSE would try and model an input variable that changes during the course of the analysis. Instead of the response being a function of a set of variables, the response would be a function of a *vector* of variables. Each vector would represent the set of decisions that could be made at each decision node. Another advantage of this formulation is that probability distributions could be applied to each possible path at each node. In this way, the human decision maker can be modeled. For example, a decision node may have two identified paths. A "practical" decision might have, say, an 80% chance of occurring while a more "aggressive" decision would only be chosen 20% of the time. In this way, one could model the personalities and decision-making abilities of several different types of decision makers, but with the ability to assess them in one modeled environment.

Finally, also at the campaign level, we address the issue of the scenario. The most useful solution is a robust solution. Yet, as mentioned earlier, the specific scenario plays a heavy role in determining the outputs. Robust solutions can be explored if a probabilistic threat environment is employed. In this way, rapidly advancing technologies can be accounted for, as well as the changing political climate. If a tactical or technological solution is found while incorporating a probabilistic scenario, then it can be claimed that the solution is robust. If, on the other hand a converged solution is not possible, then the boundaries of the problem can be properly explored and the results factored into the risk of developing such a technology or tactical situation.

Figure 12 summarizes the full probabilistic environment as applied to the linked analysis environment. The traditional RSM and DoE methods will be applied at the engineering level, with the outputs from that level (in CDF form) becoming the inputs to the mission level. Because the inputs are probabilistic, the outputs will also be probabilistic, but no internal probabilistic manipulations will occur at this level. At the campaign level, a probabilistic threat scenario is incorporated. Analysis of this scenario, using decision tree methods, will identify key decision nodes. Appropriate shape factors will be applied to these decision nodes. The final outputs will be in the form of system metrics of effectiveness, and are presented in the CDF format.

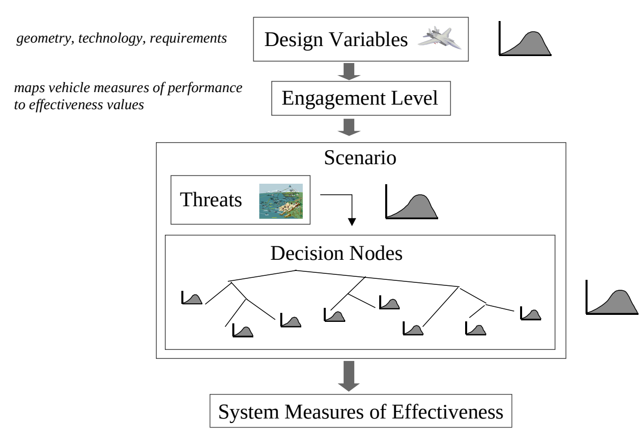

Figure 12- Proposed Full Probabilistic Environment

FUTURE WORK

The purpose of this paper was to outline the approach and identify some of the key issues associated with applying full probabilistic methods to campaign analysis. The authors are currently pursuing the application of these ideas by formulating a system effectiveness framework called POSSEM. Once completed, the framework will be applied to a test case. This test case will involve applying survivability concepts to aircraft and assessing their impact at the theater level. A fully linked analysis environment will be developed, and the probabilistic methods applied.

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